

Saturation-Tolerant Tunnel Prescribed Control for Vessel-Train Formation of Underactuated MSVs

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Abstract—The vessel-train formation composed of multiple marine surface vehicles (MSVs) is an economical and feasible mode to improve the effectiveness of waterborne transportation. This paper investigates the performance-prescribed vessel-train formation of path-guided underactuated MSVs subject to unknown kinetics, input saturation, and actuator faults. We develop a saturation-tolerant prescribed control method for implementing the vessel-train formation along a parameterized path. Specifically, at the kinematic level, a saturation-tolerant prescribed performance (SPP) function is constructed by introducing non-negative modified variables to not only restrict tracking errors but also avoid possible violations because of input saturation and actuator faults. Then, the surge and yaw tunnel guidance laws based on the transformed errors are derived to achieve position and heading tracking under SPP constraints. At the kinetic level, the saturation-tolerant control laws are designed using the identified kinetics from echo state network-based estimators. By the Lyapunov stability analysis, all error signals of the proposed closed-loop system are proven to be uniformly ultimately bounded and evolve within SPP constraints against input saturation and actuator faults. Finally, simulation results are conducted to illustrate the effectiveness of the proposed saturation-tolerant tunnel prescribed control method for vessel-train formation.

Index Terms—Actuator faults, input saturation, marine surface vehicles, tunnel prescribed performance, vessel-train formation.

I. INTRODUCTION

AS A maritime cooperation mode, the formation of marine surface vehicles (MSVs) has been an increasingly

promising trend, celebrated for its advantages in efficiency, reliabilities and robustness [1], [2], [3]. To facilitate the waterborne transportation, multiple marine vessels are deployed to form a train-like cooperative pattern called as the vessel-train formation, which is allowed to access narrow waterways [5] and [6]. A fundamental issue in implementing this specific formation is to derive the control law for every vessel to establish and sustain a predefined spatial configuration.

The formation control problem of marine vehicles has attracted considerable attention and yielded diverse research results, which explored various approaches including neural network [7], [8], [9], fuzzy logic system [10], [11], [12], [13], observers [14] and [15], and learning [16] and [17], etc. In [18], a graph-based coordinated path following the control method is presented for underactuated ships subject to constant disturbances. In [19], a modular cooperative path maneuvering controller is developed to form the multi-vessel queue formation between two virtual leaders along an open curve. As an expansion of [19], [20] proposes a ring-networked control scheme for the symmetric formation on a closed curve. To accommodate width-varying waterways, [21] proposes a formation scaling control method based on bearing rigidity theory. To enhance the flexibility of formation, [22] investigates a two-level distributed time-varying formation control architecture under the fixed topology. Note that the aforementioned results pay more attention to the cooperative mission but ignore the control performance. In [23], the performance indices of MSVs with individual objectives are studied to reach the Nash equilibrium using the noncooperative game. Under the game framework, [24] and [25] present the distributed optimal formation results for fully-actuated MSVs. Though these schemes in [18], [19], [20], [21], [22], [23], [24], [25] can be employed to implement the vessel-train formation, it ensures that tracking errors converge to a size-unknown residual set. When operating on narrow waterways such as inland waterways and sea-river, it is both worthwhile and critical to explicitly preconfigure the convergence rate, overshoot, and steady-state accuracy for MSVs.

Known for being effective tools to configure performance indices in prior, prescribed performance control (PPC) in [26] and funnel control (FC) in [27] are proposed to restrict the system state or tracking error within a predefined small residual set. Over the past decade, a variety of applications and evolutions of the standard PPCs and FCs have been reported in the formation control problem. Specifically, [28] and [29] consider the limited

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sensing range for MSVs and define the collision avoidance- and connectivity maintenance-related PPC constraints for the leader-follower formation control. Similar to the performance functions in [28] and [29], [30] develops a robust formation control method using only relative distance and angle among MSVs. The state-feedback PPC schemes in [28], [29], [30] rely on the velocity signals of marine vehicles from sensors or networks. To get rid of dependence on the velocity, some velocity-estimated control schemes are derived to achieve the velocity-unavailable performance-guaranteed formation such as high-gain observers [31] and [32], fuzzy state observers [33] and [34], and disturbance observers [35] and [36]. To further enhance the property of convergence time, [37], [38], [39] improve the traditional performance functions as the finite-time PPC with the presetting time convergence. Besides the convergence time, it is desirable to guarantee the small overshoot of the dynamic system in [40] and [41]. Different from the above schemes, the prescribed performance objective can be achieved by formulating a quadratic program problem subject to control barrier function-based constraints. Model uncertainties and environmental disturbances are considered in the mentioned control schemes. For marine vehicles, it is also inevitable that thrusters are subject to the input saturation [44] and potential faults [45]. The impact of saturation may cause the formation error to exceed the performance function envelopes, leading to undesirable behaviors or even potential instabilities. In [42], [43], fault-tolerant tracking control methods are derived for the formation of MSVs with both actuator faults and PPC constraints. In [46] and [47], the smooth switching function is employed to avoid the possible violation owing to the input saturation. In practical applications, the mentioned methods are seldom directly employed in vessel-train formation since MSVs are usually governed by surge and yaw actuators and are not equipped with sway ones. Note that control methods proposed in [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [42], [43], [45], [46], [47] do not take into account both input saturation and actuator faults in the performance-guaranteed formation of MSVs.

This paper focuses on the tunnel prescribed control for the vessel-train formation of uncertain underactuated MSVs with input saturation and actuator faults. The main contributions of this paper are summarized as below.

- Compared with the existing formation control methods proposed in [18], [19], [20], [21], this paper develops a saturation-tolerant tunnel prescribed control method that both achieves the vessel-train formation of underactuated MSVs and guarantees the predefined performance under input saturation and actuator faults. The path-guided control scheme enables decoupling cooperation and tracking objectives to enhance the flexibility of the formation.
- Compared with existing PPCs and FCs in [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [39], [40], [42], [43], [45], [46] with standard envelopes, we design saturation-tolerant prescribed performance (SPP) functions to impose more strict and flexible performance constraints on underactuated MSVs. Under the tuning of auxiliary systems, the presented SPP not only achieves a



Fig. 1. Illustration of the vessel-train formation on waterways.

small overshoot but also autonomously scales the behavior boundaries against the input saturation.

- Different from saturation or fault compensation schemes, we derive the saturation-tolerant surge and yaw control laws for underactuated MSVs using echo state network-based (ESN-based) estimators, which can ensure that the formation errors evolve within the SPP envelopes in the presence of unknown kinetics, input saturation, and actuator faults.

Notations: Let $\mathbb{I}_{1:n}$ be an integer set $\{1, \dots, n\}$. $\mathbf{0}_{m \times n}$ represents an $m \times n$ -dimensional zero matrix. $\text{diag}\{\cdot\}$ is a block-diagonal matrix. $\|\cdot\|$ denotes the Euclidean norm of a vector or matrix. $\bar{\lambda}(\cdot)$ and $\underline{\lambda}(\cdot)$ represent the maximum and minimum eigenvalues of a matrix, respectively.

II. PROBLEM FORMULATION

Consider a vessel-train formation containing one super leader and N follower MSVs depicted in Fig. 1. In reference to body-fixed reference frame $\{B\}$ and earth-fixed reference frame $\{E\}$, the motion dynamics of MSV i for $i \in \mathbb{I}_{1:N}$ is expressed as [48]

$$\begin{cases} \dot{x}_i = u_i \cos \psi_i - v_i \sin \psi_i \\ \dot{y}_i = u_i \sin \psi_i + v_i \cos \psi_i \\ \dot{\psi}_i = w_i \\ m_{iu} \dot{u}_i = f_{iu}(u_i, v_i, w_i) + \tau_{iu} + \tau_{iu}^d \\ m_{iv} \dot{v}_i = f_{iv}(u_i, v_i, w_i) + \tau_{iv}^d \\ m_{iw} \dot{w}_i = f_{iw}(u_i, v_i, w_i) + \tau_{iw} + \tau_{iw}^d \end{cases} \quad (1)$$

where $\mathbf{p}_i = [x_i, y_i]^\top \in \mathbb{R}^2$ is the position and $\psi_i \in \mathbb{R}$ is the yaw angle in $\{E\}$. $u_i, v_i, w_i \in \mathbb{R}$ denote the surge, sway, and yaw velocities in $\{B\}$, respectively. $f_{iu}(\cdot), f_{iv}(\cdot), f_{iw}(\cdot) \in \mathbb{R}$ are unknown functions governed by Coriolis/centripetal force and hydrodynamic damping effects. $m_{iu}, m_{iv}, m_{iw} \in \mathbb{R}^+$ are inertia masses. $\tau_{iu}^d, \tau_{iv}^d, \tau_{iw}^d \in \mathbb{R}$ are bounded environmental disturbances caused by wind, wave, and current; $\tau_{iu}, \tau_{iw} \in \mathbb{R}$ denote the surge force and yaw moment, respectively. In practice, the actuators of MSVs may suffer from the input saturation and fault, which can be modeled by

$$\tau_{ij} = \gamma_{ij}(t, t_0) h_{ij}(\tau_{ij}^s) + \tau_{ij}^f(t, t_1), \quad j = u, w \quad (2)$$

where $\gamma_{ij}(t, t_0) \in \mathbb{R}$ is an actuator effectiveness with t_0 being the initial time. $\tau_{ij}^f(t, t_1)$ represents the additive fault segment with $t_1 \in \mathbb{R}^+$. $h_{ij}(\tau_{ij}^s)$ is a nonlinear saturation function described by

$$h_{ij}(\tau_{ij}^s) = \begin{cases} \bar{\tau}_{ij}, & \tau_{ij}^s \geq \bar{\tau}_{ij} \\ \tau_{ij}^s, & \underline{\tau}_{ij} \leq \tau_{ij}^s \leq \bar{\tau}_{ij} \\ \underline{\tau}_{ij}, & \tau_{ij}^s \leq \underline{\tau}_{ij} \end{cases} \quad (3)$$

where τ_{ij}^s is the desired control signal. $\bar{\tau}_{ij}, \underline{\tau}_{ij} \in \mathbb{R}$ are the upper and lower bounds.

In the vessel-train formation, consider N virtual leaders moving along a predefined path $\mathbf{p}_d(\theta_i) = [x_d(\theta_i), y_d(\theta_i)]^\top \in \mathbb{R}^2$ with $\theta_i \in \mathbb{R}$ being a path parameter for $i \in \mathbb{I}_{1:N}$. The dynamics of θ_i is presented by $\dot{\theta}_i = v_s - \varpi_i$, where v_s is the update speed of the super leader θ_0 and ϖ_i is a cooperative error to be designed later. Through the communication, the path information is delivered to every MSV, and the line-of-sight distance and heading error of MSV i are defined as

$$\begin{cases} z_{ip} = \sqrt{(x_d(\theta_i) - x_i)^2 + (y_d(\theta_i) - y_i)^2} \\ z_{i\psi} = \psi_{id} - \psi_i \end{cases} \quad (4)$$

where $\psi_{id} = \text{atan2}(y_d(\theta_i) - y_i, x_d(\theta_i) - x_i)$ represents the line-of-sight angle. Note that ψ_{id} is not well-defined when $z_{ip} = 0$ because $\text{atan2}(\cdot, \cdot)$ is not defined at $(0, 0)$. In the subsequent, the controller for the vessel-train formation will be designed such that ψ_{id} is well-defined for $\forall t \geq 0$.

Note that the fact $x_d(\theta_i) - x_i = z_{ip} \cos \psi_{id}$ and $y_d(\theta_i) - y_i = z_{ip} \sin \psi_{id}$. Then, it yields from (1) and (4) that

$$\begin{cases} \dot{z}_{ip} = (x_d^\theta \cos \psi_{id} + y_d^\theta \sin \psi_{id})\dot{\theta}_i - u_i \cos z_{i\psi} - v_i \sin z_{i\psi} \\ \dot{z}_{i\psi} = \dot{\psi}_{id} - w_i \end{cases}$$

with $x_d^\theta = \partial x_d / \partial \theta_i$ and $y_d^\theta = \partial y_d / \partial \theta_i$.

Since the underactuated MSV is not equipped with sway thrusters, the subsequent design focuses on the dynamics

$$\begin{cases} \dot{z}_{ip} = (x_d^\theta \cos \psi_{id} + y_d^\theta \sin \psi_{id})\dot{\theta}_i - u_i \cos z_{i\psi} - v_i \sin z_{i\psi} \\ \dot{z}_{i\psi} = \dot{\psi}_{id} - w_i \\ m_{iu}^* \dot{u}_i = F_{iu} + \tau_{iu} \\ m_{iw}^* \dot{w}_i = F_{iw} + \tau_{iw} \end{cases} \quad (5)$$

where m_{iu}^* and m_{iw}^* are nominal inertia parameters to relax the requirement of the full knowledge of m_{iu} and m_{iw} [49]. $F_{iu} = m_{iu}^* (f_{iu}(u_i, v_i, w_i) + \tau_{iu} + \tau_{iu}^d) / m_{iu} - \tau_{iu}$ and $F_{iw} = m_{iw}^* (f_{iw}(u_i, v_i, w_i) + \tau_{iw} + \tau_{iw}^d) / m_{iw} - \tau_{iw}$.

Remark 1: The controller development for underactuated MSV employs a polar coordinate transformation technique, which is usually used to deal with the underactuation of marine vehicles in [31] and [50].

The performance index to be explicitly prespecified is desirable and crucial for vessel-train formation of underactuated MSVs sailing on waterways. Because of the property of small overshoots, tunnel prescribed performance (TPP) functions are employed to restrict z_{ip} and $z_{i\psi}$ such that

$$-z_{ip}^l < z_{ip} < z_{ip}^r \quad (6)$$

$$-z_{i\psi}^l < z_{i\psi} < z_{i\psi}^r \quad (7)$$

for $\forall t \geq 0$, where

$$\begin{cases} z_{ik}^r = (\delta_{ik}^r + \text{sgn}(z_{ik,0}))\rho_{ik}(t) - \rho_{ik,\infty} \text{sgn}(z_{ik,0}) \\ z_{ik}^l = (\delta_{ik}^l - \text{sgn}(z_{ik,0}))\rho_{ik}(t) + \rho_{ik,\infty} \text{sgn}(z_{ik,0}) \\ \rho_{ik}(t) = (\rho_{ik,0} - \rho_{ik,\infty})e^{-\mu_{ik}t} + \rho_{ik,\infty} \end{cases} \quad (8)$$

with $\rho_{ik,0} = \rho_{ik}(0)$, $\rho_{ik,\infty} = \lim_{t \rightarrow \infty} \rho_{ik}(t)$, $\rho_{ik,0} > \rho_{ik,\infty} > 0$, $\mu_{ik} \in \mathbb{R}^+$, $0 \leq \delta_{ik}^r, \delta_{ik}^l \leq 1$, and $z_{ik,0} = z_{ik}(0)$ for $k = p, \psi$. From the definition of z_{ip} , it has $z_{ip} \geq 0$ for $\forall t \geq 0$. Thus, the lower boundary function for z_{ip} is formulated as $z_{ip}^l = 0$ to ensure the good definition of ψ_{id} . With the aid of TPP constraints defined by (6)–(8), the performance indices of z_{ip} and $z_{i\psi}$ can be explicitly given by

- *convergence rate:* faster than the decay rate $-\mu_{ik}$;
- *bounds of overshoots:* $\{-z_{ip}^l(0), z_{ip}^r(0)\}$ and $\{-z_{i\psi}^l(0), z_{i\psi}^r(0)\}$;
- *steady-state accuracy:* $\max\{0, |z_{ip}^r(\infty)|\}$ and $\max\{|z_{i\psi}^r(\infty)|, |z_{i\psi}^l(\infty)|\}$.

This paper focuses on how to achieve the vessel-train formation with prescribed performance for a group of underactuated MSVs suffered from actuator saturation and actuator faults. Herein, a saturation-tolerant tunnel control method is developed to achieve the following objectives. Specifically,

- *Geometric objective:* Drive the MSV i to follow the path $\mathbf{p}_d(\theta_i)$ such that

$$\lim_{t \rightarrow \infty} |z_{ip}| < \epsilon_{ip} \in \mathbb{R}^+, \quad \lim_{t \rightarrow \infty} |z_{i\psi}| < \epsilon_{i\psi} \in \mathbb{R}^+. \quad (9)$$

Moreover, the tracking errors z_{ip} and $z_{i\psi}$ evolve within TPP constraint spaces when $h_{ij} = \tau_{ij}^s$.

- *Dynamic objective:* To govern the sailing velocity and spatial configuration, the following objectives are satisfied

$$\begin{cases} \lim_{t \rightarrow \infty} |\dot{\theta}_i - v_s| \leq \epsilon_{i\theta 1} \in \mathbb{R}^+ \\ \lim_{t \rightarrow \infty} |\theta_i - \theta_0 - \theta_{i0}| \leq \epsilon_{i\theta 2} \in \mathbb{R}^+ \end{cases} \quad (10)$$

where θ_{i0} is a scalar deviation of path parameters with respect to the super leader. The neighbor distances of the vessel-train formation can be determined by θ_{i0} .

To move on, the following assumptions and lemma are need.

Assumption 1 ([51]): For marine vessels, there exist positive constants $\underline{\gamma}_{ij} \in \mathbb{R}$ and $\bar{\tau}_{ij}^f \in \mathbb{R}$ such that $\underline{\gamma}_{ij} \leq \gamma_{ij}(t, t_0) \leq 1$ and $|\tau_{ij}^f(t, t_1)| \leq \bar{\tau}_{ij}^f$ for $i \in \mathbb{I}_{1:N}$ and $j = u, w$.

Assumption 2: For the TPP constraints (6)–(7), the initial conditions are satisfied such that $z_{ip}(0) \in (0, z_{ip}^r(0))$ and $z_{i\psi}(0) \in (-z_{i\psi}^l(0), z_{i\psi}^r(0))$ at $t = 0$ for $i \in \mathbb{I}_{1:N}$.

Lemma 1 ([52]): Consider a system $\dot{x}(t) = Kx(t) + u(t)$ with the state $x \in \mathbb{R}^m$, the Metzler matrix $K \in \mathbb{R}^{m \times m}$, and the nonnegative input $u(t) \in \mathbb{R}^m$ for $x(0) \in \mathbb{R}^m$ and $\forall t \geq 0$. If $x(0) \geq 0$, the solution of system is unique such that $x(t) \geq 0$ holds for all $t \geq 0$.

III. CONTROLLER DESIGN

In this section, we propose a saturation-tolerant tunnel prescribed control method including the SPPs, auxiliary systems, tunnel guidance laws, path update law, ESN-based estimators,

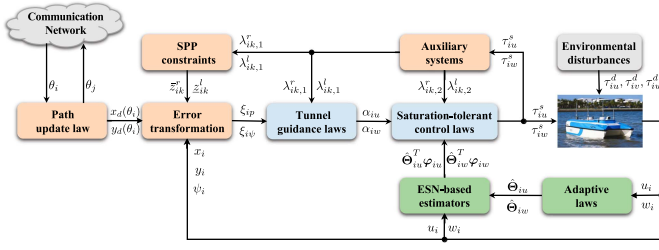


Fig. 2. Diagram block of the developed saturation-tolerant tunnel prescribed control scheme.

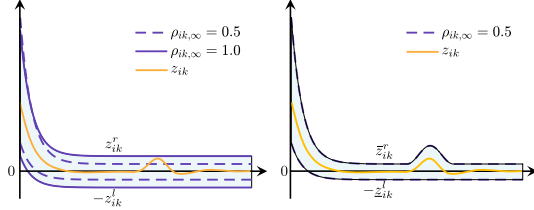


Fig. 3. Comparison illustrations of TPP and SPP.

and saturation-tolerant control laws. The Diagram block of the proposed method is presented in Fig. 2.

A. Design of Tunnel Guidance Laws

Based on TPP functions (8), we construct the SPP functions with flexible envelopes as follows

$$\bar{z}_{ik}^r = z_{ik}^r + \lambda_{ik,1}^r, \quad \bar{z}_{ik}^l = z_{ik}^l + \lambda_{ik,1}^l \quad (11)$$

where \$\lambda_{ik,1}^r \in \mathbb{R}_{\geq 0}\$ and \$\lambda_{ik,1}^l \in \mathbb{R}_{\geq 0}\$ are to enhance the tolerance for the error fluctuation caused by input saturation.

According to (2) and (3), the tuning mechanism of the SPP is given by the auxiliary system

$$\begin{cases} \dot{\lambda}_{ik,1}^r = -(\mathcal{F}_{ik}^r)^{-1} \mathcal{F}_{ik}(-\ell_{ik,1} \lambda_{ik,1}^r + \lambda_{ik,2}^r) \\ \dot{\lambda}_{ik,1}^l = -(\mathcal{F}_{ik}^l)^{-1} \mathcal{F}_{ik}(\ell_{ik,1} \lambda_{ik,1}^l - \lambda_{ik,2}^l) \\ \dot{\lambda}_{ik,2}^r = -\ell_{ik,2} \lambda_{ik,2}^r + \bar{\tau}_{ik}^a \\ \dot{\lambda}_{ik,2}^l = -\ell_{ik,2} \lambda_{ik,2}^l + \bar{\tau}_{ik}^a \\ \bar{\tau}_{ik}^a = \frac{1}{2m_{ij}^*} (\text{sgn}(\tau_{ij}^s - \bar{\tau}_{ij}) + 1)(\tau_{ij}^s - \bar{\tau}_{ij}) \\ \bar{\tau}_{ik}^a = \frac{1}{2m_{ij}^*} (\text{sgn}(\tau_{ij}^s - \bar{\tau}_{ij}) - 1)(\tau_{ij}^s - \bar{\tau}_{ij}) \end{cases} \quad (12)$$

with \$\lambda_{ik,1}^r(0) = \lambda_{ik,1}^l(0) = \lambda_{ik,2}^r(0) = \lambda_{ik,2}^l(0) = 0\$, where \$\lambda_{ik,2}^r, \lambda_{ik,2}^l \in \mathbb{R}\$ are states of auxiliary system. \$\mathcal{F}_{ik}, \mathcal{F}_{ik}^r, \mathcal{F}_{ik}^l \in \mathbb{R}\$ are partial derivatives to be defined later. \$\ell_{ik,1}, \ell_{ik,2} \in \mathbb{R}\$ are positive gains.

Remark 2: In practice, it usually needs to predeploy quantitative parameters \$\rho_{ik,0}\$ and \$\rho_{ik,\infty}\$ according to the specified requirement. However, the presence of input saturation and actuator fault may cause tracking errors to violate the given performance constraints since standard PPCs [53], FCs [54], and TPPs [33] can not adaptively adjust their boundaries against input saturation and actuator faults. Thus, it has to enlarge the parameter \$\rho_{ik,\infty}\$ to tolerate the fluctuating errors, which is illustrated by an example in Fig. 3. Inspired by [55] and [56], SPP is designed to improve the flexibility and tolerance of boundary

functions against input saturation. It is seen from Fig. 3 that the upper bound \$\bar{z}_{ik}^r\$ of the designed SPP can be scaled to tolerate the fluctuating errors. Under no input saturation, the TPP constraints defined by (6)–(8) are held. Thus, the tuning mechanism is effective in guaranteeing the stability of the vessel-train formation of marine vessels subject to input saturation and actuator faults.

To satisfy the constraint (11), \$z_{ik}\$ is mapped as an unconstrained variable \$\xi_{ik}\$ via the error transformation function formulated as follows

$$z_{ik} = \frac{\bar{z}_{ik}^r + \bar{z}_{ik}^l}{2} \Upsilon(\xi_{ik}) + \frac{\bar{z}_{ik}^r - \bar{z}_{ik}^l}{2} \quad (13)$$

where \$\Upsilon(\xi_{ik})\$ is a smooth and strictly increasing function, called as error transformation function, with three essential properties: \$\lim_{\xi_{ik} \rightarrow \infty} \Upsilon(\xi_{ik}) = 1\$, \$\lim_{\xi_{ik} \rightarrow -\infty} \Upsilon(\xi_{ik}) = -1\$, and \$\Upsilon(0) = 0\$.

Then, the transformed variable \$\xi_{ik}\$ is yielded by taking the inverse function of \$\Upsilon(\xi_{ik})\$ as

$$\xi_{ik} = \Upsilon^{\text{inv}}(z_{ik}, \bar{z}_{ik}^r, \bar{z}_{ik}^l) = \tan\left(\frac{\pi}{2} \Upsilon(\xi_{ik})\right) \quad (14)$$

where \$\Upsilon(\xi_{ik}) = 2 \arctan(\xi_{ik})/\pi\$. Then, it differentiates \$\xi_{ik}\$ along with (13) and (14) as follows

$$\dot{\xi}_{ik} = \mathcal{F}_{ik} \dot{z}_{ik} + \mathcal{F}_{ik}^r \dot{\bar{z}}_{ik}^r + \mathcal{F}_{ik}^l \dot{\bar{z}}_{ik}^l \quad (15)$$

with \$\mathcal{F}_{ik} = \pi \sec^2(\pi \Upsilon(\xi_{ik})/2) / (\bar{z}_{ik}^r + \bar{z}_{ik}^l)\$, \$\mathcal{F}_{ik}^r = -\pi \sec^2(\pi \Upsilon(\xi_{ik})/2) (z_{ik} + \bar{z}_{ik}^l) / (\bar{z}_{ik}^r + \bar{z}_{ik}^l)^2\$, and \$\mathcal{F}_{ik}^l = -\pi \sec^2(\pi \Upsilon(\xi_{ik})/2) (z_{ik} - \bar{z}_{ik}^r) / (\bar{z}_{ik}^r + \bar{z}_{ik}^l)^2\$.

Based on (11), derivatives of \$\xi_{ip}\$ and \$\xi_{i\psi}\$ are deduced as

$$\begin{cases} \dot{\xi}_{ip} = \mathcal{F}_{ip} \dot{z}_{ip} + \mathcal{F}_{ip}^r (\dot{z}_{ip}^r + \dot{\lambda}_{ip,1}^r) + \mathcal{F}_{ip}^l \dot{\lambda}_{ip,1}^l \\ \dot{\xi}_{i\psi} = \mathcal{F}_{i\psi} \dot{z}_{i\psi} + \mathcal{F}_{i\psi}^r (\dot{z}_{i\psi}^r + \dot{\lambda}_{i\psi,1}^r) + \mathcal{F}_{i\psi}^l (\dot{z}_{i\psi}^l + \dot{\lambda}_{i\psi,1}^l) \end{cases} \quad (16)$$

Substituting (5) into (16) yields

$$\begin{cases} \dot{\xi}_{ip} = \mathcal{F}_{ip} ((x_d^0 \cos \psi_{id} + y_d^0 \sin \psi_{id})(v_s - \varpi_i) - \alpha_{iu} - u_{ie} + 2u_i \sin^2 \frac{z_{i\psi}}{2} - v_i \sin z_{i\psi}) + \mathcal{F}_{ip}^r \dot{z}_{ip}^r + \mathcal{F}_{ip}^l (\ell_{ip,1} (\lambda_{ip,1}^r - \lambda_{ip,1}^l) - \lambda_{ip,2}^r + \lambda_{ip,2}^l) \\ \dot{\xi}_{i\psi} = \mathcal{F}_{i\psi} (-\alpha_{iw} - w_{ie} + \dot{\psi}_{id}) + \mathcal{F}_{i\psi}^r \dot{z}_{i\psi}^r + \mathcal{F}_{i\psi}^l \dot{z}_{i\psi}^l + \mathcal{F}_{i\psi} (\ell_{i\psi,1} (\lambda_{i\psi,1}^r - \lambda_{i\psi,1}^l) - \lambda_{i\psi,2}^r + \lambda_{i\psi,2}^l) \end{cases} \quad (17)$$

with \$u_{ie} = u_i - \alpha_{iu}\$ and \$w_{ie} = w_i - \alpha_{iw}\$, where \$\alpha_{iu}\$ and \$\alpha_{iw}\$ are the desired surge and yaw guidance laws to be designed, respectively.

To achieve the evolution within the SPP constraints defined by (11), the tunnel guidance laws \$\alpha_{iu}\$ and \$\alpha_{iw}\$ based on (12) are designed as

$$\begin{cases} \alpha_{iu} = (x_d^0 \cos \psi_{id} + y_d^0 \sin \psi_{id}) \dot{\theta}_i - v_i \sin \psi_{ie} + 2u_i \sin^2 \frac{z_{i\psi}}{2} + \mathcal{F}_{ip}^{-1} (k_{ip} \xi_{ip} + \mathcal{F}_{ip}^r \dot{z}_{ip}^r) + \ell_{ip,1} (\lambda_{ip,1}^r - \lambda_{ip,1}^l) \\ \alpha_{iw} = \dot{\psi}_{id} + \mathcal{F}_{i\psi}^{-1} (k_{i\psi} \xi_{i\psi} + (\mathcal{F}_{i\psi}^r \dot{z}_{i\psi}^r + \mathcal{F}_{i\psi}^l \dot{z}_{i\psi}^l)) + \ell_{i\psi,1} (\lambda_{i\psi,1}^r - \lambda_{i\psi,1}^l) \end{cases} \quad (18)$$

where \$k_{ip}\$ and \$k_{i\psi}\$ are positive constants.

In the following, the path update law is developed to coordinate multiple MSVs for a vessel-train formation. Under an

undirected network environment, the coordination variable ϖ is derived as

$$\varpi_i = k_{i\theta} \left(\sum_{j=1}^N a_{ij} (\theta_i - \theta_j - \theta_{ij0}) + a_{i0} (\theta_i - \theta_0 - \theta_{i0}) \right) \quad (19)$$

with $\theta_{ij0} = \theta_{i0} - \theta_{j0}$, where $k_{i\theta}$ is a positive constant. a_{ij} depicts the communication link between nodes i and j for $i \neq j$, $j \in \mathbb{I}_{0:N}$. If node i receives the signal from node j , then $a_{ij} = 1$; otherwise, $a_{ij} = 0$. Additionally, the self-link of node i is $a_{ii} = 0$ for $i \in \mathbb{I}_{1:N}$.

Letting $\theta_{ie} = \theta_i - \theta_0 - \theta_{i0}$, it gets from (17) and (18) that

$$\begin{cases} \dot{\xi}_{ip} = -k_{ip}\xi_{ip} - \mathcal{F}_{ip}(u_{ie} - \lambda_{ip,2}^l + \lambda_{ip,2}^r) \\ \dot{\xi}_{i\psi} = -k_{i\psi}\xi_{i\psi} - \mathcal{F}_{i\psi}(w_{ie} - \lambda_{i\psi,2}^l + \lambda_{i\psi,2}^r) \\ \dot{\theta}_{ie} = -\varpi_i. \end{cases} \quad (20)$$

B. Design of Saturation-Tolerant Control Laws

With the aid of the approximation ability of ESNs, the ESN-based estimators are developed by (2) and (5) as follows

$$\begin{cases} \dot{\hat{u}}_i = -(\varsigma_{iu} + k_{iu}^o)(\hat{u}_i - u_i) + \hat{\Theta}_{iu}^\top \varphi_{iu} + \frac{1}{m_{iu}^*} h_{iu} \\ \dot{\hat{w}}_i = -(\varsigma_{iw} + k_{iw}^o)(\hat{w}_i - w_i) + \hat{\Theta}_{iw}^\top \varphi_{iw} + \frac{1}{m_{iw}^*} h_{iw} \end{cases} \quad (21)$$

where $\hat{u}_i$ and $\hat{w}_i$ denote the estimation velocities. $\varsigma_{iu} \in \mathbb{R}^+$, $\varsigma_{iw} \in \mathbb{R}^+$, $k_{iu}^o \in \mathbb{R}^+$, and $k_{iw}^o \in \mathbb{R}^+$ are the estimator coefficients. $\hat{\Theta}_{iu}$ and $\hat{\Theta}_{iw}$ are the estimated weights of ESNs. $\varphi_{iu} \in \mathbb{R}^m$ and $\varphi_{iw} \in \mathbb{R}^m$ are reservoir states updated by

$$\begin{cases} \dot{\varphi}_{iu} = T_{iu}^{-1}(-b_{iu}\varphi_{iu} + \sigma_{iu}(\Theta_{iu}^x \chi_{iu} + \Theta_{iu}^\varphi \varphi_{iu})) \\ \dot{\varphi}_{iw} = T_{iw}^{-1}(-b_{iw}\varphi_{iw} + \sigma_{iw}(\Theta_{iw}^x \chi_{iw} + \Theta_{iw}^\varphi \varphi_{iw})) \end{cases} \quad (22)$$

where $T_{iu} \in \mathbb{R}^+$ and $T_{iw} \in \mathbb{R}^+$ are time constants; $b_{iu} \in \mathbb{R}^+$ and $b_{iw} \in \mathbb{R}^+$ represent leaking rates; $\sigma_{iu}(\cdot) \in \mathbb{R}^m$ and $\sigma_{iw}(\cdot) \in \mathbb{R}^m$ are activation functions; $\chi_{iu} = [u_i(t), u_i(t - t_d), h_{iu}(t)]^\top$ and $\chi_{iw} = [w_i(t), w_i(t - t_d), h_{iw}(t)]^\top$ denote the input vectors of ESNs with the sampling interval $t_d \in \mathbb{R}^+$; $\Theta_{iu}^x \in \mathbb{R}^{m \times 3}$, $\Theta_{iw}^x \in \mathbb{R}^{m \times 3}$, $\Theta_{iu}^\varphi \in \mathbb{R}^{m \times m}$, and $\Theta_{iw}^\varphi \in \mathbb{R}^{m \times m}$ are the input and reservoir weights, respectively.

To update $\hat{\Theta}_{iu}$, and $\hat{\Theta}_{iw}$, the adaptive laws are designed as

$$\begin{cases} \dot{\hat{\Theta}}_{iu} = -\Gamma_{iu} \left(\varphi_{iu}(\hat{u}_i - u_i) + k_{iu}^\Theta \hat{\Theta}_{iu} \right) \\ \dot{\hat{\Theta}}_{iw} = -\Gamma_{iw} \left(\varphi_{iw}(\hat{w}_i - w_i) + k_{iw}^\Theta \hat{\Theta}_{iw} \right) \end{cases} \quad (23)$$

where $k_{iu}^\Theta \in \mathbb{R}$, $k_{iw}^\Theta \in \mathbb{R}$, $\Gamma_{iu} \in \mathbb{R}$, and $\Gamma_{iw} \in \mathbb{R}$ are positive tuning coefficients.

Letting $\tilde{u}_i = \hat{u}_i - u_i$, $\tilde{w}_i = \hat{w}_i - w_i$ be the estimation errors, it renders along (5) and (21) that

$$\begin{cases} \dot{\tilde{u}}_i = -(\varsigma_{iu} + k_{iu}^o)\tilde{u}_i + \frac{h_{iu} - \tau_{iu} - F_{iu}}{m_{iu}^*} + \hat{\Theta}_{iu}^\top \varphi_{iu} \\ \dot{\tilde{w}}_i = -(\varsigma_{iw} + k_{iw}^o)\tilde{w}_i + \frac{h_{iw} - \tau_{iw} - F_{iw}}{m_{iw}^*} + \hat{\Theta}_{iw}^\top \varphi_{iw} \end{cases} \quad (24)$$

Define $q_{iu} = \tilde{u}_i - \alpha_{iu} + \lambda_{ip,2}^r - \lambda_{ip,2}^l$ and $q_{iw} = \tilde{w}_i - \alpha_{iw} + \lambda_{i\psi,2}^r - \lambda_{i\psi,2}^l$ and take their derivatives with

(12) and (21) as

$$\begin{cases} \dot{q}_{iu} = -(\varsigma_{iu} + k_{iu}^o)\tilde{u}_i + \hat{\Theta}_{iu}^\top \varphi_{iu} + \frac{h_{iu}}{m_{iu}^*} - \dot{\alpha}_{iu} \\ \quad - \ell_{ip,2}(\lambda_{ip,2}^r - \lambda_{ip,2}^l) + (\bar{\tau}_{iu}^a - \mathcal{I}_{iu}^a) \\ \dot{q}_{iw} = -(\varsigma_{iw} + k_{iw}^o)\tilde{w}_i + \hat{\Theta}_{iw}^\top \varphi_{iw} + \frac{h_{iw}}{m_{iw}^*} - \dot{\alpha}_{iw} \\ \quad - \ell_{i\psi,2}(\lambda_{i\psi,2}^r - \lambda_{i\psi,2}^l) + (\bar{\tau}_{iw}^a - \mathcal{I}_{iw}^a). \end{cases} \quad (25)$$

Then, it yields from (2) and (3) that $h_{iu} = m_{iu}^*(\mathcal{I}_{iu}^a - \bar{\tau}_{iu}^a) + \tau_{iu}^s$ and $h_{iw} = m_{iw}^*(\mathcal{I}_{iw}^a - \bar{\tau}_{iw}^a) + \tau_{iw}^s$. The saturation-tolerant control laws are designed as

$$\begin{cases} \tau_{iu}^s = m_{iu}^* \left(-k_{iu}q_{iu} - \hat{\Theta}_{iu}^\top \varphi_{iu} + \dot{\alpha}_{iu} \right. \\ \quad \left. + \mathcal{F}_{ip}\xi_{ip} + \ell_{ip,2}(\lambda_{ip,2}^r - \lambda_{ip,2}^l) \right) \\ \tau_{iw}^s = m_{iw}^* \left(-k_{iw}q_{iw} - \hat{\Theta}_{iw}^\top \varphi_{iw} + \dot{\alpha}_{iw} \right. \\ \quad \left. + \mathcal{F}_{i\psi}\xi_{i\psi} + \ell_{i\psi,2}(\lambda_{i\psi,2}^r - \lambda_{i\psi,2}^l) \right) \end{cases} \quad (26)$$

where k_{iu} and k_{iw} are the positive constants.

Combining (25) with (26), one has

$$\begin{cases} \dot{q}_{iu} = -k_{iu}q_{iu} - (\varsigma_{iu} + k_{iu}^o)\tilde{u}_i + \mathcal{F}_{ip}\xi_{ip} \\ \dot{q}_{iw} = -k_{iw}q_{iw} - (\varsigma_{iw} + k_{iw}^o)\tilde{w}_i + \mathcal{F}_{i\psi}\xi_{i\psi}. \end{cases} \quad (27)$$

IV. STABILITY ANALYSIS

This section analyzes the property of auxiliary system (12) and the stability of the closed-loop system.

A. Analysis of Auxiliary System

The property of auxiliary system (12) is stated by the following lemma.

Lemma 2: Consider the MSVs with dynamics (1), the SPP (11), the auxiliary system (12), and the ETF (13). If the inequality $|\tau_{ij}^s - h_{ij}| \leq \bar{h}_{ij}$ with $h_{ij} > 0$ and TPP constraints (6) and (7) hold for $\forall t \geq 0$, then $0 \leq \lambda_{ik,1}^r, \lambda_{ik,1}^l \leq \ell_{ik,1}^{-1} \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$ and $0 \leq \lambda_{ik,2}^r, \lambda_{ik,2}^l \leq \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$ for $k = p, \psi$ and $j = u, w$.

Proof: Given that $\lambda_{ik,2}^r(0), \lambda_{ik,2}^l(0)$ are non-negative and $\ell_{ik,2}$ is positive, we have $\lambda_{ik,2}^r \geq 0$ and $\lambda_{ik,2}^l \geq 0$ from Lemma 1. Furthermore, the inequality $|\tau_{ij}^s - h_{ij}| \leq \bar{h}_{ij}$ implies that $\bar{\tau}_{ik}^a \leq \bar{h}_{ij}/m_{ij}^*$. Subsequently, (12) indicates that the dynamics of $\lambda_{ik,2}^r$ is governed by $\dot{\lambda}_{ik,2}^r \leq -\ell_{ik,2}\lambda_{ik,2}^r + \bar{h}_{ij}/m_{ij}^*$. When $\lambda_{ik,2}^r \geq \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$, it results in $\dot{\lambda}_{ik,2}^r \leq 0$, which means that $0 \leq \lambda_{ik,2}^r \leq \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$. Similarly, the following inequality $0 \leq \lambda_{ik,2}^l \leq \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$ is also deduced.

Moreover, it follows from (11) and (13) that both $(\mathcal{F}_{ik}^r)^{-1} \mathcal{F}_{ik} \ell_{ik,1}$ and $(\mathcal{F}_{ik}^l)^{-1} \mathcal{F}_{ik} \ell_{ik,1}$ are positive. Referencing Lemma 1 again, it confirms that $\lambda_{ik,1}^r \geq 0$ and $\lambda_{ik,1}^l \geq 0$. Since $\lambda_{ik,2}^r \leq \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$, the evolution of $\lambda_{ik,1}^r$ is described by $\dot{\lambda}_{ik,1}^r \leq -(\mathcal{F}_{ik}^r)^{-1} \mathcal{F}_{ik} (-\ell_{ik,1}\lambda_{ik,1}^r + \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*)$. It is clear that $\dot{\lambda}_{ik,1}^r \leq 0$ for $\lambda_{ik,1}^r \geq \ell_{ik,1}^{-1} \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$. Therefore, it renders that $0 \leq \lambda_{ik,1}^r \leq \ell_{ik,1}^{-1} \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$. An similar bound is derived for $\lambda_{ik,1}^l$, namely, $0 \leq \lambda_{ik,1}^l \leq \ell_{ik,1}^{-1} \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$.

In summary, auxiliary variables $\lambda_{ik,1}^r, \lambda_{ik,1}^l, \lambda_{ik,2}^r$, and $\lambda_{ik,2}^l$ are bounded by $0 \leq \lambda_{ik,1}^r, \lambda_{ik,1}^l \leq \ell_{ik,1}^{-1} \ell_{ik,2}^{-1} \bar{h}_{ij}/m_{ij}^*$ and $0 \leq$

$\lambda_{ik,2}^r, \lambda_{ik,2}^l \leq \ell_{ik,2}^{-1} \bar{h}_{ij} / m_{ij}^*$ for $k = p, \psi$ and $j = u, w$. This completes the property analysis of auxiliary system (12).

B. Stability of Closed-Loop System

The stability of the closed-loop system consisting of (20), (24), and (27) is given as follows.

Theorem 1: For a vessel-train formation composed of N underactuated MSVs (1) subject to input saturation and actuator faults, if Assumptions 1 and 2 hold, then under the auxiliary system (12), guidance laws (18), ESN-based estimators (21), adaptive laws (23), and saturation-tolerant control laws (26), all of the MSV in the formation are regulated to a small neighboring region of the parameterized path. Moreover, formation tracking errors do not violate SPP constraints despite input saturation and actuator faults.

Proof: The stability analysis is concluded via the following three steps.

B. Step 1: Choose a Lyapunov function candidate $V_0 = 0.5 \sum_{i=1}^N (\tilde{u}_i^2 + \tilde{w}_i^2 + \|\tilde{\Theta}_{iu}\|^2 / \Gamma_{iu} + \|\tilde{\Theta}_{iw}\|^2 / \Gamma_{iw})$ for the subsystem (24) with $\tilde{\Theta}_{iu} = \hat{\Theta}_{iu} - \Theta_{iu}$ and $\tilde{\Theta}_{iw} = \hat{\Theta}_{iw} - \Theta_{iw}$, where $\Theta_{iu} \in \mathbb{R}^m$ and $\Theta_{iw} \in \mathbb{R}^m$ are output weights satisfying $\|\Theta_{iu}\| \leq \bar{\Theta}_{iu} \in \mathbb{R}^+$ and $\|\Theta_{iw}\| \leq \bar{\Theta}_{iw} \in \mathbb{R}^+$.

By utilizing the approximation ability of ESNs, unknown functions in (5) are presented as $F_{iu}/m_{iu}^* = \Theta_{iu}^\top \varphi_{iu} + \epsilon_{iu}$ and $F_{iw}/m_{iw}^* = \Theta_{iw}^\top \varphi_{iw} + \epsilon_{iw}$, where ϵ_{iu} and ϵ_{iw} denote approximation errors satisfying $|\epsilon_{iu}| \leq \bar{\epsilon}_{iu} \in \mathbb{R}^+$ and $|\epsilon_{iw}| \leq \bar{\epsilon}_{iw} \in \mathbb{R}^+$. Then, it follows from (23) that

$$\begin{cases} \hat{\Theta}_{iu}^\top \varphi_{iu} - F_{iu}/m_{iu}^* = \tilde{\Theta}_{iu}^\top \varphi_{iu} - \epsilon_{iu} \\ \hat{\Theta}_{iw}^\top \varphi_{iw} - F_{iw}/m_{iw}^* = \tilde{\Theta}_{iw}^\top \varphi_{iw} - \epsilon_{iw} \\ \dot{\hat{\Theta}}_{iu} = -\Gamma_{iu}(\varphi_{iu} \tilde{u}_i + k_{iu}^o \hat{\Theta}_{iu}) \\ \dot{\hat{\Theta}}_{iw} = -\Gamma_{iw}(\varphi_{iw} \tilde{w}_i + k_{iw}^o \hat{\Theta}_{iw}). \end{cases} \quad (28)$$

With (2), (24), and (28), it takes the derivative of V_0 as

$$\begin{aligned} \dot{V}_0 = \sum_{i=1}^N & \left(-(\varsigma_{iu} + k_{iu}^o) \tilde{u}_i^2 + \frac{1}{m_{iu}^*} \left((1 - \gamma_{iu}) h_{iu} - \tau_{iu}^f \right) \tilde{u}_i \right. \\ & - (\varsigma_{iw} + k_{iw}^o) \tilde{w}_i^2 + \frac{1}{m_{iw}^*} \left((1 - \gamma_{iw}) h_{iw} + \tau_{iw}^f \right) \tilde{w}_i \\ & \left. - k_{iu}^o \tilde{\Theta}_{iu}^\top \hat{\Theta}_{iu} - k_{iw}^o \tilde{\Theta}_{iw}^\top \hat{\Theta}_{iw} - \tilde{u}_i \epsilon_{iu} - \tilde{w}_i \epsilon_{iw} \right). \end{aligned} \quad (29)$$

From Young's inequality and Assumption 1, one gets $-\tilde{u}_i \epsilon_{iu} \leq \frac{1}{2}(\tilde{u}_i^2 + \epsilon_{iu}^2)$, $-\tilde{w}_i \epsilon_{iw} \leq \frac{1}{2}(\tilde{w}_i^2 + \epsilon_{iw}^2)$, $((1 - \gamma_{iu}) h_{iu} - \tau_{iu}^f) \tilde{u}_i \leq \frac{1}{2}((1 - \gamma_{iu})^2 h_{iu}^2 + \tau_{iu}^{f2}) + \tilde{u}_i^2$, $((1 - \gamma_{iw}) h_{iw} + \tau_{iw}^f) \tilde{w}_i \leq \frac{1}{2}((1 - \gamma_{iw})^2 h_{iw}^2 + \tau_{iw}^{f2}) + \tilde{w}_i^2$, $-k_{iu}^o \tilde{\Theta}_{iu}^\top \hat{\Theta}_{iu} \leq -\frac{1}{2} k_{iu}^o (\|\tilde{\Theta}_{iu}\|^2 - \|\Theta_{iu}\|^2)$, and $-k_{iw}^o \tilde{\Theta}_{iw}^\top \hat{\Theta}_{iw} \leq -\frac{1}{2} k_{iw}^o (\|\tilde{\Theta}_{iw}\|^2 - \|\Theta_{iw}\|^2)$.

Combining (29), it yields that

$$\dot{V}_0 \leq \sum_{i=1}^N \left(-(\varsigma_{iu} + k_{iu}^o - \frac{1}{2} - \frac{1}{m_{iu}^*}) \tilde{u}_i^2 - \frac{k_{iu}^o}{2} \|\tilde{\Theta}_{iu}\|^2 \right.$$

$$\begin{aligned} & \left. - \left(\varsigma_{iw} + k_{iw}^o - \frac{1}{2} - \frac{1}{m_{iw}^*} \right) \tilde{w}_i^2 - \frac{k_{iw}^o}{2} \|\tilde{\Theta}_{iw}\|^2 \right. \\ & + \frac{1}{2} \left(\epsilon_{iu}^2 + \frac{1}{m_{iu}^*} (\tau_{iu}^{f2} + (1 - \gamma_{iu})^2 h_{iu}^2) + k_{iu}^o \|\Theta_{iu}\|^2 \right) \\ & \left. + \epsilon_{iw}^2 + \frac{1}{m_{iw}^*} (\tau_{iw}^{f2} + (1 - \gamma_{iw})^2 h_{iw}^2) + k_{iw}^o \|\Theta_{iw}\|^2 \right). \end{aligned}$$

Define $\tilde{\vartheta}_i = [\tilde{u}_i, \tilde{w}_i]^\top$ and $\tilde{\Theta}_i = [\tilde{\Theta}_{iu}^\top, \tilde{\Theta}_{iw}^\top]^\top$. If the selection of parameters ς_{iu} , k_{iu}^o , ς_{iw} , and k_{iw}^o satisfies $\varsigma_{iu} + k_{iu}^o > 1/2 + 1/m_{iu}^*$ and $\varsigma_{iw} + k_{iw}^o > 1/2 + 1/m_{iw}^*$, one has

$$\dot{V}_0 \leq \sum_{i=1}^N \left(-c_{i0} \|\tilde{\vartheta}_i\|^2 - \frac{1}{2} k_{i0} \|\tilde{\Theta}_i\|^2 + \varepsilon_i \right) \quad (30)$$

where $c_{i0} = \min\{\varsigma_{iu} + k_{iu}^o - 1/2 - 1/m_{iu}^*, \varsigma_{iw} + k_{iw}^o - 1/2 - 1/m_{iw}^*\}$, $k_{i0} = \min\{k_{iu}^o, k_{iw}^o\}$, and $\varepsilon_i = (\epsilon_{iu}^2 + \epsilon_{iw}^2 + ((1 - \gamma_{iu})^2 h_{iu}^2 + \tau_{iu}^{f2})/m_{iu}^* + ((1 - \gamma_{iw})^2 h_{iw}^2 + \tau_{iw}^{f2})/m_{iw}^* + k_{iu}^o \|\Theta_{iu}\|^2 + k_{iw}^o \|\Theta_{iw}\|^2)/2$.

B. Step 2: Denote $z_{i\theta} = \sum_{j=1}^N a_{ij}(\theta_i - \theta_j - \theta_{ij0}) + a_{i0}(\theta_i - \theta_0 - \theta_{i0})$, $z_\theta = [z_{1\theta}, \dots, z_{N\theta}]^\top$, $\theta_e = [\theta_{1e}, \dots, \theta_{Ne}]^\top$, and $\varpi = [\varpi_1, \dots, \varpi_N]^\top$. Then, it has

$$z_\theta = \mathcal{H} \theta_e, \quad \dot{\theta}_e = -\varpi. \quad (31)$$

In what follows, a Lyapunov function candidate for the subsystem (20) is chosen as $V_1 = \sum_{i=1}^N (\xi_{ip}^2 + \xi_{i\psi}^2)/2 + \theta_e^\top \mathcal{H} \theta_e/2$, whose dynamics along (19), (20), and (31) is given as follows

$$\begin{aligned} \dot{V}_1 = \sum_{i=1}^N & \left(-k_{ip} \xi_{ip}^2 - \xi_{ip} \mathcal{F}_{ip}(u_{ie} - \lambda_{ip,2}^l + \lambda_{ip,2}^r) \right. \\ & \left. - k_{i\psi} \xi_{i\psi}^2 - \xi_{i\psi} \mathcal{F}_{i\psi}(w_{ie} - \lambda_{i\psi,2}^l + \lambda_{i\psi,2}^r) - k_{i\theta} z_{i\theta}^2 \right) \\ & \leq \sum_{i=1}^N \left(-k_i \|\xi_i\|^2 - k_{i\theta} z_{i\theta}^2 + \xi_i^\top \mathcal{F}_i(\lambda_{i,2}^l - \lambda_{i,2}^r - \vartheta_{ie}) \right) \end{aligned}$$

where $k_i = \min\{k_{ip}, k_{i\psi}\}$, $\xi_i = [\xi_{ip}, \xi_{i\psi}]^\top$, $\mathcal{F}_i = \text{diag}\{\mathcal{F}_{ip}, \mathcal{F}_{i\psi}\}$, $\lambda_{i,2}^r = [\lambda_{ip,2}^r, \lambda_{i\psi,2}^r]^\top$, $\lambda_{i,2}^l = [\lambda_{ip,2}^l, \lambda_{i\psi,2}^l]^\top$, and $\vartheta_{ie} = [u_{ie}, w_{ie}]^\top$.

Based on the fact that $\lambda_{i,2}^l - \lambda_{i,2}^r - \vartheta_{ie} = \tilde{\vartheta}_i - q_i$ with $q_i = [q_{iu}, q_{iw}]^\top$, it obtains

$$\dot{V}_1 \leq \sum_{i=1}^N \left(-k_i \|\xi_i\|^2 - k_{i\theta} z_{i\theta}^2 + \xi_i^\top \mathcal{F}_i(\tilde{\vartheta}_i - q_i) \right).$$

Using the Young's inequality, it gets $\xi_i^\top \mathcal{F}_i \tilde{\vartheta}_i \leq \|\xi_i\|^2/2 + \|\mathcal{F}_i\|^2 \|\tilde{\vartheta}_i\|^2/2$, which is substituted into $\dot{V}_1$ as

$$\dot{V}_1 \leq \sum_{i=1}^N \left(-c_{i1} \|\xi_i\|^2 - k_{i\theta} z_{i\theta}^2 - \xi_i^\top \mathcal{F}_i q_i + \frac{1}{2} \|\mathcal{F}_i\|^2 \|\tilde{\vartheta}_i\|^2 \right) \quad (32)$$

where $c_{i1} = k_i - 1/2$.

B. Step 3: Choose a Lyapunov function candidate $V_2 = \sum_{i=1}^N (q_{iu}^2 + q_{iw}^2)/2$ for the subsystem (27). Then, it takes the

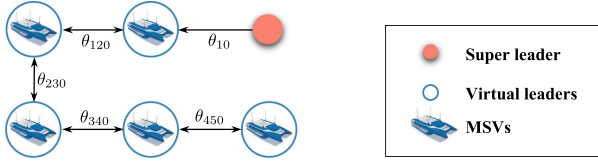


Fig. 4. The communication topology of the vessel-train formation.

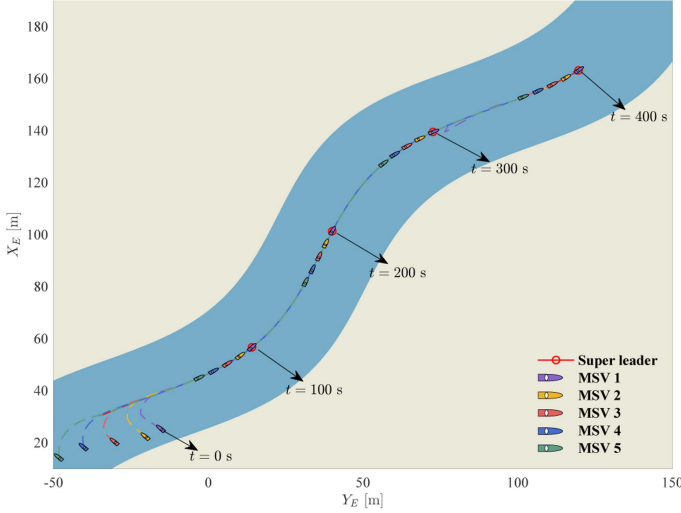


Fig. 5. A vessel-train formation along the urban river.

derivative of $\dot{V}_2$ as

$$\dot{V}_2 = \sum_{i=1}^N (-k_{iu} q_{iu}^2 - (\varsigma_{iu} + k_{iu}^o) q_{iu} \tilde{u}_i + q_{iu} \mathcal{F}_{ip} \xi_{ip} - k_{iw} q_{iw}^2 - (\varsigma_{iw} + k_{iw}^o) q_{iw} \tilde{w}_i + q_{iw} \mathcal{F}_{i\psi} \xi_{i\psi}).$$

Utilizing $-(\varsigma_{iu} + k_{iu}^o) q_{iu} \tilde{u}_i \leq (\varsigma_{iu} + k_{iu}^o)(q_{iu}^2 + \tilde{u}_i^2)/2$ and $-(\varsigma_{iw} + k_{iw}^o) q_{iw} \tilde{w}_i \leq (\varsigma_{iw} + k_{iw}^o)(q_{iw}^2 + \tilde{w}_i^2)/2$, one has

$$\begin{aligned} \dot{V}_2 \leq & \sum_{i=1}^N \left(-\left(k_{iu} - \frac{1}{2}(\varsigma_{iu} + k_{iu}^o)\right) q_{iu}^2 + \frac{1}{2}(\varsigma_{iu} + k_{iu}^o) \tilde{u}_i^2 \right. \\ & \left. - \left(k_{iw} - \frac{1}{2}(\varsigma_{iw} + k_{iw}^o)\right) q_{iw}^2 + \frac{1}{2}(\varsigma_{iw} + k_{iw}^o) \tilde{w}_i^2 \right. \\ & \left. + q_{iu} \mathcal{F}_{ip} \xi_{ip} + q_{iw} \mathcal{F}_{i\psi} \xi_{i\psi} \right). \end{aligned}$$

When $k_{iu} > (\varsigma_{iu} + k_{iu}^o)/2$ and $k_{iw} > (\varsigma_{iw} + k_{iw}^o)/2$, the derivative of V_2 is obtained as follows

$$\dot{V}_2 \leq \sum_{i=1}^N \left(-c_{i2} \|\mathbf{q}_i\|^2 + \bar{c}_{i0} \|\tilde{\boldsymbol{\theta}}_i\|^2 + \mathbf{q}_i^\top \mathcal{F}_i \boldsymbol{\xi}_i \right) \quad (33)$$

with $c_{i2} = \min\{k_{iu} - (\varsigma_{iu} + k_{iu}^o)/2, k_{iw} - (\varsigma_{iw} + k_{iw}^o)/2\}$ and $\bar{c}_{i0} = \max\{\varsigma_{iu} + k_{iu}^o, \varsigma_{iw} + k_{iw}^o\}/2$.

Consequently, the Lyapunov function of the resulting closed-loop system is presented as $V = V_0 + V_1 + V_2$. With (30), (32), and (33), the derivative of V is rendered as

$$\dot{V} \leq \sum_{i=1}^N \left(-c'_{i0} \|\tilde{\boldsymbol{\theta}}_i\|^2 - c_{i1} \|\boldsymbol{\xi}_i\|^2 - c_{i2} \|\mathbf{q}_i\|^2 - \frac{1}{2} \underline{k}_i^\Theta \|\tilde{\boldsymbol{\Theta}}_i\|^2 \right.$$

$$\left. - k_{i\theta} z_{i\theta}^2 + \varepsilon_i \right) \quad (34)$$

where $c'_{i0} = c_{i0} - \|\mathcal{F}_i\|^2/2 - \bar{c}_{i0}$.

Denote $\mathbf{E}' = [\tilde{\boldsymbol{\theta}}^\top, \boldsymbol{\xi}^\top, \mathbf{q}^\top, \tilde{\boldsymbol{\Theta}}^\top, \mathbf{z}_\theta^\top]^\top$ and $\mathbf{E} = [\tilde{\boldsymbol{\theta}}^\top, \boldsymbol{\xi}^\top, \mathbf{q}^\top, \tilde{\boldsymbol{\Theta}}^\top, \boldsymbol{\theta}_e^\top]^\top$ with $\tilde{\boldsymbol{\theta}} = [\tilde{\theta}_1^\top, \dots, \tilde{\theta}_N^\top]^\top$, $\boldsymbol{\xi} = [\boldsymbol{\xi}_1^\top, \dots, \boldsymbol{\xi}_N^\top]^\top$, $\mathbf{q} = [\mathbf{q}_1^\top, \dots, \mathbf{q}_N^\top]^\top$, and $\tilde{\boldsymbol{\Theta}} = [\tilde{\boldsymbol{\Theta}}_1^\top, \dots, \tilde{\boldsymbol{\Theta}}_N^\top]^\top$. Based on the fact that $\mathbf{E}' = \boldsymbol{\Psi} \mathbf{E}$ with

$$\boldsymbol{\Psi} = \begin{bmatrix} \mathbf{I}_{3N} \otimes \mathbf{I}_2 & \mathbf{0}_{6N \times 2Nm} & \mathbf{0}_{6N \times N} \\ \mathbf{0}_{2Nm \times 6N} & \mathbf{I}_{Nm} \otimes \mathbf{I}_2 & \mathbf{0}_{2Nm \times N} \\ \mathbf{0}_{N \times 6N} & \mathbf{0}_{N \times 2Nm} & \mathcal{H} \end{bmatrix},$$

it puts into

$$\dot{V} \leq -c \|\mathbf{E}'\|^2 + \|\varepsilon\| \leq -c \lambda_{\min}(\boldsymbol{\Psi}) \|\mathbf{E}\|^2 + \|\varepsilon\| \quad (35)$$

where $\varepsilon = [\varepsilon_1, \dots, \varepsilon_N]^\top$ and $c = \min\{c_0, c_1, c_2, c_3\}$ with $c_0 = \min\{c'_{i0}, \dots, c'_{N0}\}$, $c_1 = \min\{c_{i1}, \dots, c_{N1}\}$, $c_2 = \min\{c_{i2}, \dots, c_{N2}\}$, $c_3 = \min\{\underline{k}_i^\Theta/2, \dots, \underline{k}_N^\Theta/2\}$, and $c_4 = \min\{k_{i\theta}, \dots, k_{N\theta}\}$.

Since ϵ_{iu} , ϵ_{iw} , $\boldsymbol{\Theta}_{iu}$, and $\boldsymbol{\Theta}_{iw}$ are bounded, it follows that ε_i is also bounded under Assumption 1, which implies that ε is bounded by $\|\varepsilon\| \leq \bar{\varepsilon}$. It is derived from (35) that ξ_{ik} for $i \in \mathbb{I}_{1:N}$ and $k = p, \psi$ is bounded. According to the error transformation (13), the boundedness of ξ_{ik} renders that $-z_{ik}^l < z_{ik} < \bar{z}_{ik}^r$, i.e., $-z_{ik}^l - \lambda_{ik,1}^l < z_{ik} < \bar{z}_{ik}^r + \lambda_{ik,1}^r$. Consequently, it shows that all the tracking errors z_{ip} and $z_{i\psi}$ evolve within SPP regions regardless of input saturation, actuator faults, and unknown disturbances. Therefore, all error signals of the resulting closed-loop system are uniformly ultimately bounded. $\square$

Remark 3: Assumption 2 ensures that the transformed error ξ_{ik} , as defined in (14), is well-defined for $\forall t \geq 0$. Furthermore, satisfaction of the initial condition $z_{ip}(0) \in (0, z_{ip}^r(0))$ and $z_{i\psi}(0) \in (-z_{i\psi}^l(0), z_{i\psi}^r(0))$ yields that $V(0)$ is bounded, which further renders the boundedness of $V(t)$ for $\forall t \geq 0$. Consequently, the controller designed under initial conditions leads to $\xi_{ik} \in \mathcal{L}_\infty$, thereby fulfilling the SPP constraints. Similar initial conditions are commonly used in the PPC problems, see [26] and [28].

Remark 4: A tuning guideline of designed parameters is provided to facilitate the implementation of our proposed method. For SPP, parameters $\rho_{ik,0}$, $\rho_{ik,\infty}$, δ_{ik}^r , δ_{ik}^l , and μ_{ik} are determined by practical performance requirements. The large gains $\ell_{ik,1}$ and $\ell_{ik,2}$ improve the adjustment rate of auxiliary variables. For ESN-based estimators, parameters ς_{ij} and k_{ij}^o are chosen such that $c_{i0} > 0$. For the guidance and control parameters, k_{ip} , $k_{i\psi}$, k_{iu} , and k_{iw} should be sufficiently large to ensure $c_{i1} > 0$ and $c_{i2} > 0$. Note that if k_{ip} , $k_{i\psi}$, k_{iu} , and k_{iw} are set too high, it will results in large control efforts and undesirable behaviors. Therefore, a trade-off selection is crucial and should be considered in practice.

V. SIMULATION RESULTS

This section conducts the comparison simulations of the vessel-train formation to validate the effectiveness and superiority of the proposed method.

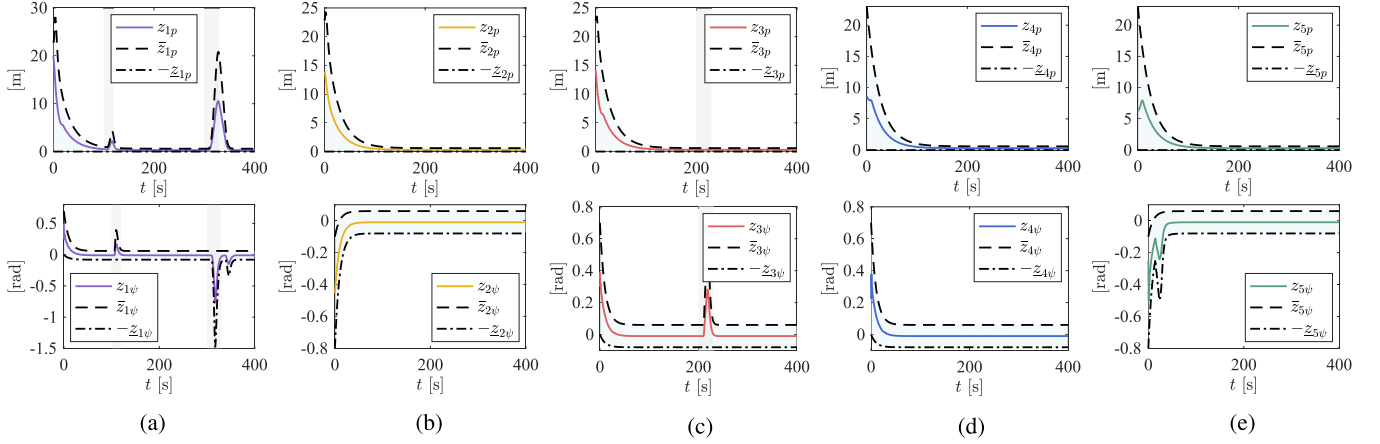


Fig. 6. Evolution of relative distances and heading errors within SPP constraint $(-z_{ik}^l, \bar{z}_{ik}^r)$, $k = p, \psi$. (a) MSV 1. (b) MSV 2. (c) MSV 3. (d) MSV 4. (e) MSV 5.

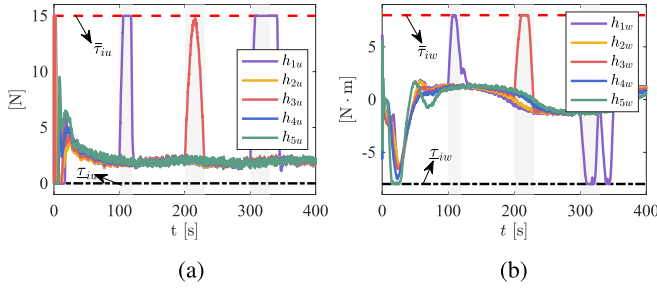


Fig. 7. Control inputs of MSVs. (a) Surge force. (b) Yaw moment.

A. Simulation Setup

For a practical scenario illustrated in Fig. 1, we consider a simulation case involving five MSVs and one super leader, whose communication topology and the predefined neighboring distances are delineated in Fig. 4. To implement the vessel-train formation, the parameterized path $p_d(\theta_i)$ is set as $p_d(\theta_i) = [\sqrt{2}\theta_i/4 - \sqrt{2}(10\cos(\theta_i/50 + \pi/3) + 40)/2, \sqrt{2}\theta_i/4 + \sqrt{2}(10\cos(\theta_i/50 + \pi/3) + 40)/2]^\top$ with initial values $\theta_1(0) = -5$, $\theta_2(0) = 15$, $\theta_3(0) = -25$, $\theta_4(0) = -35$, $\theta_5(0) = -45$, $\theta_{10} = 0$, and $\theta_{120} = \theta_{230} = \theta_{340} = \theta_{450} = 10$. In this simulation, the MSV model utilizes the marine vehicle of a length of 1.255m with detailed Bis-scale parameters referenced in [48]. The initial positions and yaw angles of five MSVs are chosen as $[-15, 25, 3\pi/4]^\top$, $[-20, 22, 3\pi/4]^\top$, $[-30, 20, 3\pi/4]^\top$, $[-40, 18, 3\pi/4]^\top$, and $[-48, 14, 3\pi/4]^\top$, sequentially, and all initial velocities are zero. The control parameters are configured as follows: $\rho_{ip,0} = 10$, $\rho_{ip,\infty} = 1$, $\rho_{i\psi,0} = 0.5$, $\rho_{i\psi,\infty} = 0.1$, $\mu_{ip} = 0.04$, $\mu_{i\psi} = 0.1$, $\delta_{ip} = \delta_{i\psi} = 0.6$, $\underline{\delta}_{ip} = \underline{\delta}_{i\psi} = 0.8$, $\ell_{ip,1} = \ell_{i\psi,1} = 0.2$, $\ell_{ip,2} = \ell_{i\psi,2} = 0.5$, $k_{ip} = 1$, $k_{i\psi} = 10$, $k_{i\theta} = 0.05$, $v_s = 1$, $T_{iu} = T_{iw} = 1$, $b_{iu} = b_{iw} = 1$, $\varsigma_{iu} = \varsigma_{iw} = 20$, $k_{iu}^o = k_{iw}^o = 1$, $\Gamma_{iu} = 1000\Gamma_{iw} = 1000$, $k_{iu}^\Theta = k_{iw}^\Theta = 0.0001$, $k_{iu} = 10$, $k_{iw} = 10$, $\bar{\tau}_{iu} = 15$, $\tau_{iu} = 0$, $\bar{\tau}_{iw} = 8$, and $\tau_{iw} = -8$. For ESNs in (22), nine neurons comprise the hidden layer, with the activation function defined

as $1/(1 + e^{-x})$. Without loss of generalities, it is assumed that MSV 1 and MSV 3 experience the following additive faults:

$$\tau_{1u}^f = \begin{cases} -13|\sin(\pi(t-100)/20)|, & t \in (100, 120) \\ -15|\sin(\pi(t-300)/30)|, & t \in (300, 330) \\ 0, & \text{others,} \end{cases}$$

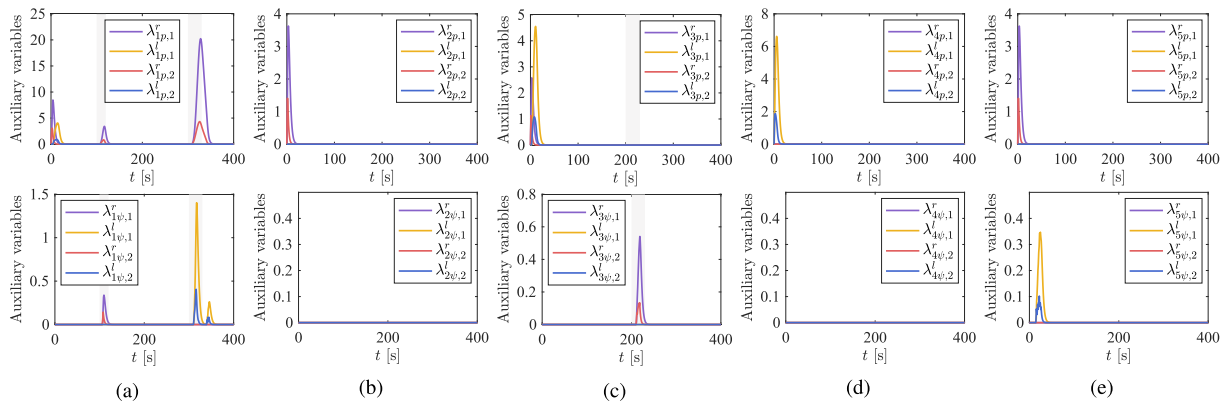
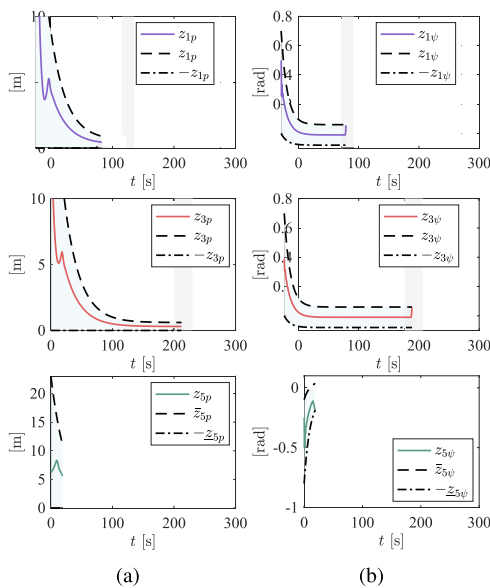
$$\tau_{1w}^f = \begin{cases} -8|\sin(\pi(t-100)/20)|, & t \in (100, 120) \\ 8.5|\sin(\pi(t-300)/30)|, & t \in (300, 330) \\ 0, & \text{others.} \end{cases}$$

$$\tau_{3u}^f = \begin{cases} -10|\sin(\pi(t-200)/30)|, & t \in (200, 230) \\ 0, & \text{others.} \end{cases}$$

$$\tau_{3w}^f = \begin{cases} -9.5|\sin(\pi(t-200)/30)|, & t \in (200, 230) \\ 0, & \text{others.} \end{cases}$$

B. Performance Illustrations

1) *Effectiveness Validation*: In this part, simulation results under the proposed saturation-tolerant vessel-train formation control method are plotted in Figs. 5–8. From motion snapshots of Fig. 5 at different instants, five MSVs form the vessel-train formation along the given parameterized path. The formation errors of all MSVs are drawn in Fig. 6, where the first and second rows display the curves of relative distances and heading errors, respectively. It is seen from Fig. 7 that, during the transient process, the surge forces of MSVs 1-3 and 5 and the yaw moment of MSV 5 reach saturation, which force the errors to converge faster than the rate $-\mu_{ik}$. It is clear that all tracking errors evolve within the SPP constraints $(-\bar{z}_{ip}, \bar{z}_{ip})$ and $(-\bar{z}_{i\psi}, \bar{z}_{i\psi})$ for $i = 1, \dots, 5$. Note that the error $z_{5\psi}$ fluctuates towards the outside of the lower boundary $-\bar{z}_{5\psi}$ owing to saturation effect. To enlarge the boundary of SPPs, the developed auxiliary system (12) generates the positive modified signals $\lambda_{5\psi,1}^l$ and $\lambda_{5\psi,2}^l$ plotted in Fig. 8(e), which enables $z_{5\psi}$ avoid the possible violation from Fig. 6(e). When the yaw saturation of MSV 5 disappears, the corresponding SPP boundary $\bar{z}_{i\psi}$ recovers



as $z_{i\psi}$ because of $\lambda_{5\psi,1}^l = \lambda_{5\psi,2}^l = 0$. In steady-state process, MSVs 1 and 3 suffer from the additive faults τ_{iu}^f and τ_{iw}^f , which lead to the saturated surge forces h_{iu} and yaw moments h_{iw} for $i = 1, 3$. According to Figs. 6(a), (e), 7(a), and (e), the resulting fluctuating errors z_{1p} , $z_{1\psi}$, and $z_{3\psi}$ still evolve within the SPP constraints regardless of actuator faults.

2) *Superiority of SPP Over TPP [57]*: This part presents a comparative analysis with the TPP-based method in [57]. For the sake of fairness, the simulation setup is the same as the SPP-based one. Simulation results of MSVs 1, 3, and 5 are displayed to illustrate the superiority of the SPP-based method. As depicted in Figs. 9 and 10, it shows that heading errors of MSV 1 and MSV 3 overpass TPP boundaries at $t = 107.63$ s and $t = 212.30$ s, respectively, owing to saturations and faults of yaw moments. Furthermore, it also finds that MSV 5 violates the TPP constraint at $t = 19.18$ s since the yaw moment is under saturation. From Figs. 6(a), (c), and (e), it is observed that the SPP boundaries have the ability to tolerate error fluctuations by introducing the

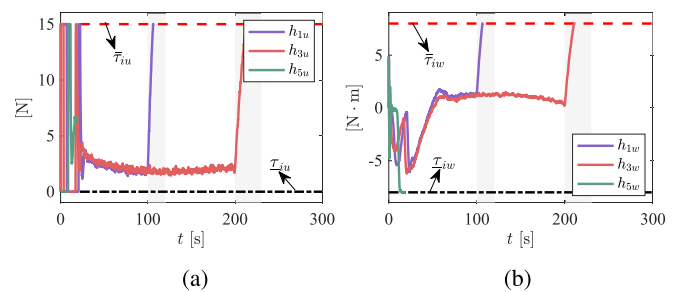


Fig. 10. Control inputs with the TPP-based method [57]. (a) Surge force. (b) Yaw moment.

VI. CONCLUSION

This paper presents a saturation-tolerant tunnel prescribed control method for the vessel-train formation of multiple underactuated MSVs subject to input saturation and actuator faults. Specifically, the designed SPP not only restrict the formation tracking errors with a smaller overshoot but also avoid possible violations under the input saturation. Using the path coordination scheme, the vessel-train formation of underactuated MSVs is achieved and formation errors are guaranteed to evolve within the prespecified SPP constraints regardless of input saturation and actuator faults. Through simulation comparisons, it demonstrates the effectiveness of the proposed saturation-tolerant tunnel prescribed control method.

REFERENCES

- [1] Z. Peng, J. Wang, D. Wang, and Q.-L. Han, "An overview of recent advances in coordinated control of multiple autonomous surface vehicles," *IEEE Trans. Ind. Informat.*, vol. 17, no. 2, pp. 732–745, Feb. 2021.
- [2] Y. Shi, C. Shen, H. Fang, and H. Li, "Advanced control in marine mechatronic systems: A survey," *IEEE/ASME Trans. Mechatron.*, vol. 22, no. 3, pp. 1121–1131, Jun. 2017.
- [3] B. Lin, W. Xie, Y. Shi, B. Du, C. Zhang, and W. Zhang, "Robust target interception strategy for a UAV with experimental validation," *IEEE Robot. Automat. Lett.*, vol. 8, no. 11, pp. 7042–7049, Nov. 2023.

- [4] Y. Cao, T. Li, and L.-Y. Hao, "Lyapunov-based model predictive control for shipboard boom cranes under input saturation," *IEEE Trans. Automat. Sci. Eng.*, vol. 20, no. 3, pp. 2011–2021, Jul. 2023.
- [5] A. Colling and R. Hekkenberg, "Waterborne platooning in the short sea shipping sector," *Transp. Res. Part C, Emerg. Technol.*, vol. 120, 2020, Art. no. 102778.
- [6] W. Wu, Z. Peng, L. Liu, and D. Wang, "A general safety-certified cooperative control architecture for interconnected intelligent surface vehicles with applications to vessel train," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 627–637, Sep. 2022.
- [7] Z. Zhao, W. He, and S. S. Ge, "Adaptive neural network control of a fully actuated marine surface vessel with multiple output constraints," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 4, pp. 1536–1543, Jul. 2014.
- [8] Y. Zhang, W. Wu, and W. Zhang, "Noncooperative game-based cooperative maneuvering of intelligent surface vehicles via accelerated learning-based neural predictors," *IEEE Trans. Intell. Veh.*, vol. 8, no. 3, pp. 2212–2221, Mar. 2023.
- [9] W. Wu, Y. Zhang, Z. Jia, J.-G. Lu, and W. Zhang, "Adaptive fault-tolerant fuzzy containment control for networked autonomous surface vehicles: A noncooperative game approach," *IEEE Trans. Fuzzy Syst.*, vol. 32, no. 7, pp. 4192–4204, Jul. 2024.
- [10] J. Li, G. Zhang, C. Liu, and W. Zhang, "COLREGs-constrained adaptive fuzzy event-triggered control for underactuated surface vessels with the actuator failures," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 12, pp. 3822–3832, Dec. 2021.
- [11] Z. Peng, J. Wang, and D. Wang, "Distributed maneuvering of autonomous surface vehicles based on neurodynamic optimization and fuzzy approximation," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 3, pp. 1083–1090, May 2018.
- [12] Y. Wang, Q. Han, M. Fei, and C. Peng, "Network-based T-S fuzzy dynamic positioning controller design for unmanned marine vehicles," *IEEE Trans. Cybern.*, vol. 48, no. 9, pp. 2750–2763, Sep. 2018.
- [13] L.-Y. Hao, H. Zhang, T.-S. Li, B. Lin, and C. L. P. Chen, "Fault tolerant control for dynamic positioning of unmanned marine vehicles based on T-S fuzzy model with unknown membership functions," *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 146–157, Jan. 2021.
- [14] Z. Peng, C. Wang, Y. Yin, and J. Wang, "Safety-certified constrained control of maritime autonomous surface ships for automatic berthing," *IEEE Trans. Veh. Technol.*, vol. 72, no. 7, pp. 8541–8552, Jul. 2023.
- [15] W. Wu, Y. Zhang, W. Zhang, and W. Xie, "Output-feedback finite-time safety-critical coordinated control of path-guided marine surface vessels based on neurodynamic optimization," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 53, no. 3, pp. 1788–1800, Mar. 2023.
- [16] Y. Zhao, Y. Ma, and S. Hu, "USV formation and path-following control via deep reinforcement learning with random braking," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 12, pp. 5468–5478, Dec. 2021.
- [17] T. Li, W. Bai, Q. Liu, Y. Long, and C. L. P. Chen, "Distributed fault-tolerant containment control protocols for the discrete-time multiagent systems via reinforcement learning method," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 8, pp. 3979–3991, Aug. 2023.
- [18] J. Ghommam and F. Mnif, "Coordinated path-following control for a group of underactuated surface vessels," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 3951–3963, Oct. 2009.
- [19] L. Liu, D. Wang, Z. Peng, and T. Li, "Modular adaptive control for LOS-based cooperative path maneuvering of multiple underactuated autonomous surface vehicles," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 47, no. 7, pp. 1613–1624, Jul. 2017.
- [20] L. Liu, D. Wang, Z. Peng, T. Li, and C. L. P. Chen, "Cooperative path following ring-networked under-actuated autonomous surface vehicles: Algorithms and experimental results," *IEEE Trans. Cybern.*, vol. 50, no. 4, pp. 1519–1529, Apr. 2020.
- [21] Y. Lu, C. Wen, T. Shen, and W. Zhang, "Bearing-based adaptive neural formation scaling control for autonomous surface vehicles with uncertainties and input saturation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 10, pp. 4653–4664, Oct. 2020.
- [22] J. Ning, T. Li, and C. P. Chen, "Neuro-adaptive distributed formation tracking control of under-actuated unmanned surface vehicles with input quantization," *Ocean Eng.*, vol. 265, 2022, Art. no. 112492.
- [23] X. Fang, G. Wen, X. Yu, and G. Chen, "Formation control for unmanned surface vessels: A game-theoretic approach," *Asian J. Control*, vol. 24, no. 2, pp. 498–509, 2022.
- [24] K. Yu, Y. Li, M. Lv, and S. Tong, "Distributed optimal formation control of multiple unmanned surface vehicles with stackelberg differential graphical game," *IEEE Trans. Artif. Intell.*, vol. 5, no. 8, pp. 4058–4073, Aug. 2024.
- [25] J. Shi and M. Ye, "Distributed optimal formation control for unmanned surface vessels by a regularized game-based approach," *IEEE/CAA J. Automatica Sinica*, vol. 11, no. 1, pp. 276–278, Jan. 2024.
- [26] C. P. Bechlioulis and G. A. Rovithakis, "Robust adaptive control of feedback linearizable MIMO nonlinear systems with prescribed performance," *IEEE Trans. Autom. Control*, vol. 53, no. 9, pp. 2090–2099, Oct. 2008.
- [27] T. Berger, H. H. Lê, and T. Reis, "Funnel control for nonlinear systems with known strict relative degree," *Automatica*, vol. 87, pp. 345–357, 2018.
- [28] S.-L. Dai, S. He, H. Lin, and C. Wang, "Platoon formation control with prescribed performance guarantees for USVs," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4237–4246, May 2018.
- [29] S. He, M. Wang, S. Dai, and F. Luo, "Leader-follower formation control of USVs with prescribed performance and collision avoidance," *IEEE Trans. Ind. Informat.*, vol. 15, no. 1, pp. 572–581, Jan. 2019.
- [30] B. S. Park and S. J. Yoo, "Connectivity-maintaining and collision-avoiding performance function approach for robust leader–follower formation control of multiple uncertain underactuated surface vessels," *Automatica*, vol. 127, 2021, Art. no. 109501.
- [31] Z. Jia, Z. Hu, and W. Zhang, "Adaptive output-feedback control with prescribed performance for trajectory tracking of underactuated surface vessels," *ISA Trans.*, vol. 95, pp. 18–26, 2019.
- [32] L. Chen, R. Cui, C. Yang, and W. Yan, "Adaptive neural network control of underactuated surface vessels with guaranteed transient performance: Theory and experimental results," *IEEE Trans. Ind. Electron.*, vol. 67, no. 5, pp. 4024–4035, May 2020.
- [33] W. Wu, Y. Zhang, W. Zhang, and W. Xie, "Distributed finite-time performance-prescribed time-varying formation control of autonomous surface vehicles with saturated inputs," *Ocean Eng.*, vol. 266, 2022, Art. no. 112866.
- [34] J. Ghommam, M. Saad, and F. Mnif, "Prescribed performances based fuzzy-adaptive output feedback containment control for multiple under-actuated surface vessels," *Ocean Eng.*, vol. 249, 2022, Art. no. 110898.
- [35] Y. Qu, W. Zhao, Z. Yu, and B. Xiao, "Distributed prescribed performance containment control for unmanned surface vehicles based on disturbance observer," *ISA Trans.*, vol. 125, pp. 699–706, 2022.
- [36] S. He, S.-L. Dai, Z. Zhao, T. Zou, and Y. Ma, "UDE-based distributed formation control for MSVs with collision avoidance and connectivity preservation," *IEEE Trans. Ind. Informat.*, vol. 20, no. 2, pp. 1476–1487, Feb. 2024.
- [37] H. Wang, M. Li, C. Zhang, and X. Shao, "Event-based prescribed performance control for dynamic positioning vessels," *IEEE Trans. Circuits Syst. II Exp. Briefs*, vol. 68, no. 7, pp. 2548–2552, Jul. 2021.
- [38] Y. Shi, W. Xie, and W. Zhang, "Sectionalized self-triggered control for AUVs with deferred quantitative constraints," *IEEE Trans. Instrum. Meas.*, vol. 73, pp. 1–10, 2024.
- [39] Y. Shi, B. Yi, W. Xie, and W. Zhang, "Enhancing prescribed performance of tracking control using monotone tube boundaries," *Automatica*, vol. 159, 2024, Art. no. 111304.
- [40] R. Ji, D. Li, S. S. Ge, and H. Li, "Tunnel prescribed control of nonlinear systems with unknown control directions," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Oct. 17, 2023, doi: [10.1109/TNNLS.2023.3322161](https://doi.org/10.1109/TNNLS.2023.3322161).
- [41] W. Wu, D. Wu, Y. Zhang, S. Chen, and W. Zhang, "Safety-critical trajectory tracking for mobile robots with guaranteed performance," *IEEE/CAA J. Automatica Sinica*, vol. 11, no. 9, pp. 2033–2035, Sep. 2024.
- [42] Y. Lu, X. Xu, L. Qiao, and W. Zhang, "Robust adaptive formation tracking of autonomous surface vehicles with guaranteed performance and actuator faults," *Ocean Eng.*, vol. 237, 2021, Art. no. 109592.
- [43] Z.-Q. Liu, Y.-L. Wang, and Q.-L. Han, "Adaptive fault-tolerant trajectory tracking control of twin-propeller non-rudder unmanned surface vehicles," *Ocean Eng.*, vol. 285, 2023, Art. no. 115294.
- [44] O. Elhaki and K. Shojaei, "Robust saturated dynamic surface controller design for underactuated fast surface vessels including actuator dynamics," *Ocean Eng.*, vol. 229, 2021, Art. no. 108987.
- [45] W. Wu, R. Ji, W. Zhang, and Y. Zhang, "Transient-reinforced tunnel coordinated control of underactuated marine surface vehicles with actuator faults," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 2, pp. 1872–1881, Feb. 2024.
- [46] Z. Zheng and M. Feroskhan, "Path following of a surface vessel with prescribed performance in the presence of input saturation and external disturbances," *IEEE/ASME Trans. Mechatron.*, vol. 22, no. 6, pp. 2564–2575, Dec. 2017.
- [47] L. N. Bikas and G. A. Rovithakis, "Prescribed performance under input saturation for uncertain strict-feedback systems: A switching control approach," *Automatica*, vol. 165, 2024, Art. no. 111663.

- [48] T. I. Fossen, *Handbook of Marine Craft Hydrodynamics and Motion Control*. Hoboken, NJ, USA: Wiley, 2011.
- [49] Y. Jiang, Z. Peng, and J. Wang, "Safety-certified multi-target circumnavigation with autonomous surface vehicles via neurodynamics-driven distributed optimization," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 54, no. 4, pp. 2092–2103, Apr. 2024.
- [50] L. Liu, D. Wang, Z. Peng, C. L. P. Chen, and T. Li, "Bounded neural network control for target tracking of underactuated autonomous surface vehicles in the presence of uncertain target dynamics," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 4, pp. 1241–1249, Apr. 2019.
- [51] R. Ji, B. Yang, J. Ma, and S. S. Ge, "Saturation-tolerant prescribed control for a class of MIMO nonlinear systems," *IEEE Trans. Cybern.*, vol. 52, no. 12, pp. 13012–13026, Dec. 2022.
- [52] L. Farina and S. Rinaldi, *Positive Linear Systems: Theory and Applications*. Hoboken, NJ, USA: Wiley, 2000, vol. 50.
- [53] B. S. Park and S. J. Yoo, "Robust trajectory tracking with adjustable performance of underactuated surface vessels via quantized state feedback," *Ocean Eng.*, vol. 246, 2022, Art. no. 110475.
- [54] X. Min, S. Baldi, W. Yu, and J. Cao, "Low-complexity control with funnel performance for uncertain nonlinear multiagent systems," *IEEE Trans. Autom. Control*, vol. 69, no. 3, pp. 1975–1982, Mar. 2024.
- [55] P. Wang, K. Yong, M. Chen, and X. Zhang, "Output-feedback flexible performance-based safe formation for underactuated unmanned surface vehicles," *IEEE Trans. Intell. Veh.*, vol. 8, no. 3, pp. 2437–2447, Mar. 2023.
- [56] W. Wu, Y. Zhang, Z. Li, J.-G. Lu, and W. Zhang, "Constrained safe cooperative maneuvering of autonomous surface vehicles: A control barrier function approach," *IEEE Trans. Syst. Man, Cybern., Syst.*, early access, Jan. 25, 2024, doi: [10.1109/TSMC.2023.3345847](https://doi.org/10.1109/TSMC.2023.3345847).
- [57] X. Bu, Q. Qi, and B. Jiang, "A simplified finite-time fuzzy neural controller with prescribed performance applied to waverider aircraft," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 7, pp. 2529–2537, Jul. 2022.